`objsegm` – User Manual

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1 Introduction

This is the user manual for the software system objsegm. It it developed to perform different kinds of segmentation. Usually the segmentation is considered as a dividing the set of image pixels into disjoint subsets or, equivalently, as an assignment of a segment name (number or label) to each pixel of the image. In doing so it is assumed, that the pixels, which belong to a particular segment, are in a certain sense "similar". The pixels, which belong to different segments, are thereby "different". In addition some prior knowledge about the segmentation itself should be often taken into account – e.g. compactness, expected shape of segment boundaries etc. Depending on the chosen dissimilarity measure, different kinds of segmentation can be distinguished – e.g. threshold methods, texture segmentation etc. However, we would like to point out, that the segmentation itself is initially defined without any respect to some dissimilarity measure. The aim of the system objsegm is not to perform some particular kind of segmentation, but rather to allow the user to build and to apply *different complex segmentation models* based on some relatively small number of "base models".

This document is not an "user manual" in a usual sense, but rather something between an "user manual" and a "programmers manual". The reason for that is, that in case of segmentation (to be able to use the system) it is absolutely necessary to understand not only, what the system does, but also how does it work.

Technically the system is implemented as a library. The software package consists of a couple of precompiled libraries (compiled under Linux with gcc 4.1.2), header files and a simple program objsegm_simple, which illustrates the usage of the system (is given as source code). We used Qt4 library by Trolltech. To compile the program objsegm_simple, do the following:

– Download objsegm_<arch>.tgz, where <arch> is your architecture,

– Unpack it e.g. by `tar -xzf objsegm_<arch>.tgz`,

– Go to the directory `objsegm_<arch>/objsegm_simple`,

– Run `qmake-qt4` followed by `make`

If all went right the executable `objsegm_simple` occurs in the current directory.

The rest of the user manual is organized as follows:

– In the next section we recall briefly the theoretical background of our approach.

– In section 3 an overview of system parts will be given (in 3.1) as well as an explanation, how a complex segmentation model can be built using base models (in 3.2).

– Section 4 contains the detailed description of system elements.

– In section 5 the interface part of the system will be explained – how to set parameters, visualize the results etc.

– Finally we give in section 6 examples, which illustrate the usage of the system and the program `objsegm_simple`.

2 Theoretical background

In this section we recall briefly the theoretical background, which our approach is based on. More detailed considerations can be found e.g. in the following sources:

– Labeling problems: [8, 13, 2, 4, 11];

– Gibbs Sampler: [6, 9];

– Expectation-Maximization algorithm: [14, 1];

– Applications: [3, 5, 7, 10, 12].

Our approach is based on statistical modeling by Gibbs probability distributions. Let us consider this in a little bit more detail on an example of a very simple segmentation model. Let R be the set of pixels of an image and K be the set of segments (labels). The segmentation is then a mapping $f : R \to K$, that assigns a label from K to each

pixel $r \in R$ of the image. In statistical modelling the a-priori probability distribution of segmentations is often assumed to be a Gibbs probability distribution of second order:

$$p(f) \sim \prod_{rr' \in E} g_{rr'}\big(f(r), f(r')\big). \tag{1}$$

Here $E \subset R \times R$ is the set of pairs of pixels, which are defined to be neighbors (we use in particular the 4-neighborhood); $f(r) \in K$ denotes the label, chosen by the segmentation f in a node $r \in R$; functions $g : K \times K \to \mathbb{R}^+$ are quality functions, which mirror assumptions for the a-priori probability distribution of segmentations (for instance the Potts model with $g(k, k') = \exp[a \cdot \mathbb{1}(k = k')]$[1] is suitable for segmentation tasks).

Let the conditional probability distribution for observations given a labeling be conditionally independent, i.e.

$$p(x \mid f) = \prod_{r \in R} q_r\big(f(r), x(r)\big), \tag{2}$$

where $x : R \to X$ is the mapping, which maps the set of pixels into the set X of color values, i.e. the image, functions $q : K \times X \to \mathbb{R}^+$ are local conditional probability distributions $p(x \mid k)$ to observe color value x given a label k.

The segmentation task can be posed in such models as a Bayes decision task with respect to a cost function $C(f, f')$ as follows:

$$f^* = \arg\min_f \sum_{f'} p(f' \mid x) \cdot C(f, f'). \tag{3}$$

Using of the additive delta cost function

$$C(f, f') = \sum_{r \in R} \mathbb{1}\big(f(r) \neq f'(r)\big) \tag{4}$$

leads to the following decision strategy:

$$f^*(r) = \arg\max_{k \in K} p\big(f(r) = k \mid x\big), \quad \text{where} \tag{5}$$

$$p\big(f(r) = k \mid x\big) \sim \sum_{f : f(r) = k} p(f, x) \tag{6}$$

Unfortunately there are no known closed solutions to compute the marginal probability distributions $p\big(f(r) = k \mid x\big)$. Therefore we use Gibbs Sampler to estimate these probabilities approximately.

[1] $\mathbb{1}(expr) = 1$ if $expr$ is true and 0 otherwise.

Besides of technical problems (approximate solutions), there are also many modeling problems. First of all, simple observation models like (2) do not allow to model segments adequately, if the appearances of the segments are complex themselves (e.g. if one segment is a texture). To overcome this difficulty it is often necessary to extend the label set K by something in addition to take into account the look of each particular segment (see e.g. [12]). Consequently the (less or more) general segmentation model (1) becomes dependent on a particular application.

Let us consider briefly a technical aspect, namely the implementation of the Gibbs Sampler for a simple segmentation model (1) and (2). To perform the generation by the Gibbs Sampler it is necessary to calculate in a pixel r the following "local" conditional probability distribution:

$$p_r(k) \sim q_r\big(k, x(r)\big) \cdot \prod_{r':rr' \in E} g_{rr'}\big(k, f(r')\big). \tag{7}$$

It is easy to see, that it is thereby not necessary "to know" the observation x, it is only necessary to know the values of the function $q_r\big(k, x(r)\big)$ at the position r for all segments k. Let us imagine, that each segment $k \in K$ is represented in the implementation by a "black box", that gives the values of q_r depending (somehow) on the actual position r and the observed image x. Then the generation according to (7) could be obviously performed. The Gibbs Sampler does not need to know even the types of the used segments – conditionally independent probability distributions of grayvalues, textures, Gaussians or whatever. The types of segments can be even different. Moreover, one "black box" can be a segmentation model (like (1)) itself. It allows to connect segmentation models hierarchically, building a tree-like structure of models.

The main idea of the system `objsegm` is the exploration of the fact, described above. The system consists of a relatively small number of "base models". Each model is able to give for all pixels of the processed image values, which can be interpreted as probabilities of observation in these pixels. Segmentation models use these values to perform segmentation, taking into account in addition their a-priori probability distribution of segmentations.

Another topic, that should be necessarily taken into account, is the following. Each base model has (sometimes many) free parameters. When building a complex model from the base ones, the number of free parameters in the whole model becomes very large. Consequently there should be a possibility to learn them either in superwised or in unsupervised manner. We use mainly Expectation-Maximization schemes (derived for each particular base model) to do that.

One of very important modeling problems is the fact, that in the scope of labeling formulation it is very difficult to use prior knowledge about the form of segments. This

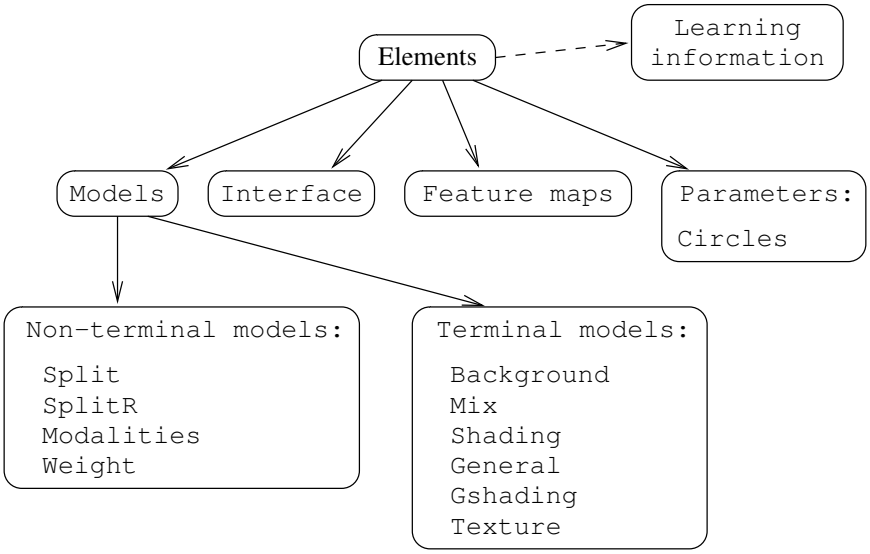


Figure 1: Hierarchy of elements.

is the case, because as a rule such information can not be incorporated into the model "in a local manner". To overcome this problem, some mechanism should be defined, that allows "to influent segmentation model non-locally". In our approach one such method is realized. It is based on the assumption, that such non-local additional information can be in principle seen as an unknown parameter of the probability distribution. The estimation of this unknown parameter can be then performed according for instance to the Maximum Likelihood principle.

3 Overview

3.1 Elements

In this subsection we give an overview of the parts of the system `objsegm`. We call these parts "elements". The classification/hierarchy of elements is illustrated in fig. 1. The most essential part of the system consists of base `models`. They are divided into two groups.

– `Non-terminal models` (or shortly `non-terminals`) perform different types of segmentations as well as some other kinds of "linking together" for other models.

– `Terminal models` (or shortly `terminals`) correspond to different types of segments.

Each model performs its own kind of optimization. For some of them a generation procedure is necessary to estimate statistics, needed to perform optimization steps (for example in a (1)-like segmentation model Gibbs Sampler should take place to estimate marginal probabilities). Summarizing, the optimization/generation algorithm for each model consists of an infinite loop, so that in each iteration some activities are performed (e.g. one optimization step). We call such a type of optimization/generation procedure "working loop".

`Parameters` represent non-local prior information for segmentation models. We decided to define parameters as a separate element to realize a certain flexibility of the whole system – one segmentation model can use many parameters, a particular type of parameters can be used for different models etc. The behavior of parameters is similar to the behavior of models – they have their own optimization procedure (working loop), which consists of an infinite loop of optimization iterations.

`Feature maps` (or shortly `maps`) are responsible for loading of the input images and performing of some preprocessing steps (e.g. convertion, normalizing etc.). Since these elements do preprocessing only, they have no working loop – i.e. all activities are performed before the working loops of the used models/parameters start.

`Learning information` is a static data block, which should be specified manually (if present) in advance. It allows to fix segments at some places of the processed image. We will distinguish in further the learning information from other elements, because this information can not be seen as a part of a complex model. It is rather "an additional input" for the system (like the input images). Therefore we will use in further the notation "element" having in mind all parts of the system (presented in fig. 1) besides of the learning information.

`Interface` is a system for storing and visualization of the results. It provides a feedback only, i.e. it does not influent the behavior of the system.

3.2 Building of a complex model

A complex model is a tree-like structure, where the leafs are terminal models and interior nodes are non-terminal ones. The connections between elements in a complex model are illustrated in fig. 2 .

– Each non-terminal model has children, which may be either terminals or non-terminals. A non-terminal model has access to all its children as well as to its parent.

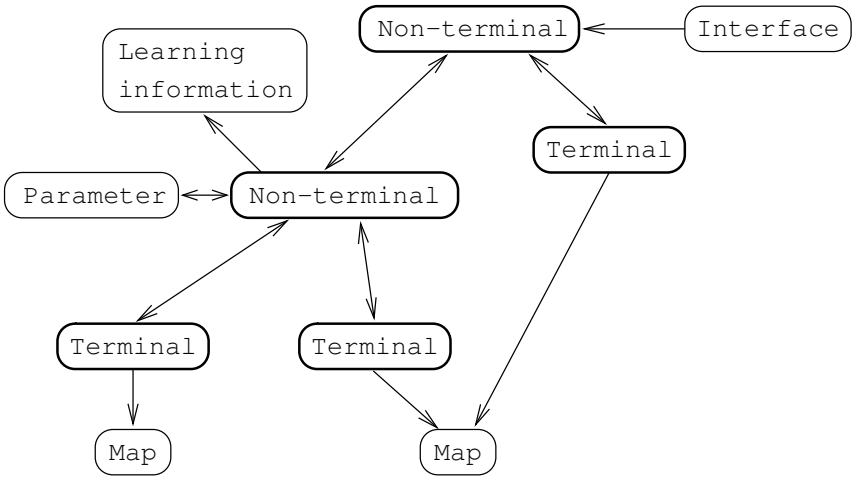


Figure 2: Complex model.

– Non-terminals may have parameters. Models have access to their parameters. Parameters have access to the models, to which they are attached.

– Non-terminal models may have an associated block of learning information.

– Each terminal model refers to exactly one feature map. Many terminals can refer to one map. Terminals have access to their parents.

– Interface object is attached to the root of the model tree. Each model has its interface functions. The interface object can call all interface functions of the model tree.

4 Detailed description

In this section we give a detailed description of elements. The majority of elements have their options. Thereby some of them are common for all (or for a certain subset) of elements. Other are specific ones. At this place we would like to note, that the system `objsegm` is still under development. We think, that at this stage it is much more important to specify the connections between the elements, rather then to fully implement certain models. In this situation it is common, that not all elements, implemented so far, fully support all options, which are foreseen yet. Let us suppose, that there is an option, which is intended to be common for a certain subset of elements. But may be not for all elements from this subset this option is relevant. In spite of this situation we would like to

present options as they are at the moment, apart from whether they are supported/used by particular elements or not.

We prefer to describe firstly the options themselves. In doing so we will follow the hierarchy of the elements (see fig. 1). After that we explain, how to set the options for each particular element of a complex model.

The majority of options have less or more reasonable default values. They will be given together with the corresponding options in form
`<option>=<default value>`.

4.1 Options, common for all elements

`Name`
: Each element should be named. `Name` is a symbol string without empty spaces. Names provide a way to identify elements, therefore they should be unique (otherwise the behavior of the system is unpredictable). At the moment this option is not relevant for `Interface`, because it need not be identified/accessed by other elements of the system. `Interface` obtains a "dummy" default name. For all other elements this option is mandatory.

`reset_policy=31`
: Each element can be reset once awhile during the work. One reason for that could be for example a program, that segments a sequence of images rather then a single image (in particular this option is not used in the program `objsegm_simple`). This option is a bitwise mask, which controls the behavior of the element, when resetting. Each element interprets this option in its own way. At the moment this option is supported by `SplitR`, `Shading`, `Gshading` and `Circles`.

4.2 Feature maps

They represent features, which are computed from input images in advance. Basically one feature is a real number. The feature map is an array of real values, that has the same sizes as the image. Their options are:

`File`
: The filename of the image, from which the feature should be computed. Mandatory.

`code=0`
: This options defines, which feature should be computed. At the moment the following possibilities are realized:
  0 features are graylevels of the image pixels,
  1 features are taken from the red channel,
  2 features are taken from the green channel,
  3 features are taken from the blue channel,
  4 experimental (images are stored in a special format).

`align=-1.`
: If not equal -1, the values of the feature map are shifted to have the mean value equal `align`.

4.3 Parameters

In contrast to models, which are less or more general, `parameters` are specific for each particular application. So far we have implemented only one type of such non-local parameter, namely `Circles`. Therefore at the moment we have no specification of options for this element.

4.4 Options, common for all models

`Type`
: This option determines, which model is used. Should be one of the following: `Split`, `SplitR`, `Modalities`, `Weight`, `Background`, `Mix`, `Shading`, `Gshading`, `General`, `Texture`. Mandatory option.

`Parent`
: This defines the name of the parent for the model in a complex model. If it is not given, the object is assumed to be a root of the model tree.

The following three options control the behavior of the working loop. One iteration of the loop consists of successive calls of the following procedure:

1. Perform optimization/generation step,
2. Once per `n_update` iterations perform an update step,
3. Adjust `timeout`,
4. Wait `timeout` milliseconds.

All working loops of the whole complex model work in parallel (technically, `objsegm` is realized as a multithreaded system). Each working loop performs a kind of indirect synchronization by adjustment of its `timeout` (time to sleep). The adjustment procedure follows the principle: "The number of iterations performed by me so far should be similar to the number of iterations performed so far by my parent". `timeout` of the root remains constant.

`n_update=0`
: This option controls, how often an update-procedure is called during the working loop. The default value `0` means "never". Such an update-procedure is implemented yet only for `Split`, `General` and `Texture`. Thereby it has almost no influence in `Split` and `General` (the default situation "never update" is suitable in most cases). The update-procedure of `Texture` in contrast contains a learning step. Therefore the default value causes situation, that the texture parameters are not learned at all. Obviously it is only reasonable, if the used texture is pre-learned in advance (see `Texture` description for details).

`timeout=10`
: This option sets the *initial* timeout for the working loop.

`min_timeout=1`
: This option sets the lower limit for the timeout of the working loop.

4.5 Options, common for terminal models

`Map`
: Each terminal model should refer to exactly one `Map`. This option sets the name of the map, which the model refers to. It is mandatory.

4.6 Options, common for non-terminal models

There are no such options.

4.7 Model overview

In this subsection a more detailed description of models is given.

4.7.1 Non-terminal models

`Split`

This model performs segmentation according to the Potts model. It means, that the quality function $g_{rr'}$ in (1) is

$$g(k,k') = \begin{cases} a & \text{if } k = k' \\ 1 & \text{otherwise} \end{cases} \tag{8}$$

(position independent). The model uses the Gibbs Sampler to estimate marginal a-posteriori probabilities of labels in each pixel. The decision for each pixel is done according to (5). At the moment this model does not support `parameters`. The only one option is

`potts=10.`

Potts parameter a in (8).

`SplitR`

This is an extention of the Potts model. The state set K is supposed to be ordered, i.e. states are enumerated from 1 to $|K|$. The functions g_{rr} are just the same as for the model "Split" except that jumps greater then 1 are disabled in addition:

$$g(k,k') = \begin{cases} a & \text{if } k = k' \\ 1 & \text{if } |k - k'| = 1 \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

At the moment this model dos not support the `learning information`. It supports `parameters`. Just as in the previous case there is only one option

`potts=10.`

Potts parameter a in (9).

Modalities

This is a "transitional" model, which is used to combine many conditional probability distributions to one under the assumption, that the original distributions are conditionally independent. The model performs nothing other, but multiplication of probabilities, given by its children:

$$p\big(x(r) \mid f(r)\big) = \prod_i p_i\big(x(r) \mid f(r)\big), \tag{10}$$

where i is the index for children models. This Model has no options. One iteration of the working loop consists of simply recalculation of probability values for all pixels according to (10).

Weight

This model is used to compute a weighted sum of probabilities, given by its children:

$$p\big(x(r) \mid f(r)\big) = \sum_i w_i \cdot p_i\big(x(r) \mid f(r)\big), \tag{11}$$

where i is the index for children models, the weights w_i satisfy $w_i \geq 0$, $\sum_i w_i = 1$. A simple example for this model is the Gaussian mixture – the children are Gaussians in that case. The weights w_i are learned during the working loop. The new values of w_i are computed as a convex combination of the old ones and the "best ones", which are estimated by an EM-like schema:

$$w_i^{(new)} = w_i^{(old)} \cdot (1 - \gamma) + w_i^{(best)} \cdot \gamma, \tag{12}$$

i.e. a step in the gradient ascent direction is performed. The options are:

`step=0.1`
: The speed of learning, i.e. γ in (12).

`w(<i>)=1.`
: Initial values for w_i. The index `<i>` can vary from 0 to $n-1$, where n is the number of children models. After all parameters are set, the weights are normalized to sum to 1.

4.7.2 Terminal models

Background

This terminal model realizes the Gaussian probability distribution for features. Let $x(r)$

be the value of the used feature (stored in the associated `Map`) in a pixel r. This model computes

$$p\big(x(r)\big) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{\big(x(r)-\mu\big)^2}{2\sigma^2}\right], \tag{13}$$

where μ is the mean value and σ is the dispersion. During the working loop the values of μ and σ are learned in a gradient ascent way as follows:

$$\begin{aligned} \mu^{(new)} &= \mu^{(old)} \cdot (1-\gamma) + \mu^{(best)} \cdot \gamma \\ \sigma^{(new)} &= \sigma^{(old)} \cdot (1-\gamma) + \sigma^{(best)} \cdot \gamma \cdot \lambda \end{aligned} \tag{14}$$

Here are $\mu^{(best)}$ and $\sigma^{(best)}$ the "actual best" values, which are estimated according to the Maximum Likelihood principle, γ is the step size, λ is an heuristic parameter, which allow to control the behavior of the dispersion. The options are:

`mean=128.`
: The *initial* value of μ.

`sigma=1000.`
: The *initial* value for $2\sigma^2$.

`step=0.1`
: The step size, i.e. γ in (14).

`l_q=1.`
: The value of λ in (14). As already said, this option is an heuristic one, i.e. the use of other values than 1 is theoretically not grounded. For example use of $\lambda > 1$ causes the dispertion to be greater, as the "real" one. Use other then the default values with care.

`Mix`

This model realizes a Gaussian mixture. It is in a certain sense obsolete, because the same family of probability distributions can be realized by `Weight` together with a couple of `Backgrounds`. The probabilities $p\big(x(r)\big)$ are computed by

$$p\big(x(r)\big) = \sum_{i=1}^{n} w_i \cdot \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{\big(x(r)-\mu_i\big)^2}{2\sigma_i^2}\right], \tag{15}$$

where n is the number of Gaussians in the mixture, other notations have the same meaning as in `Weight` and `Background`. The weights w_i are learned in the same way as in `Weight`, i.e. by (12), the mean values μ_i and dispersions σ_i in the same way as in `Background`, i.e. by (14). The options are:

`ng=2`
: The number of Gaussians in the mixture.

`step=0.1`
: The step size γ.

`m(<i>)=128.`
: The initial mean value μ_i for the i-th Gaussian. The index `<i>` vary from 0 to $n-1$.

`s(<i>)=1000.`
: The initial value of $2\sigma_i^2$ for the i-th Gaussian.

`w(<i>)=1.`
: The initial weight w_i for the i-th Gaussian. After all options are set, the weights are normalized to sum to 1.

`l(<i>)=1.`
: The parameter λ_i for the i-th Gaussian.

`General`

This model realizes a general discrete probability distribution $p(x)$. The values of the feature x (stored in the associated `Map`) are thereby rounded to the closest integer value and cut to the range 0 to 255 (initially, this model was designed to represent probability distributions of grayvalues). Speaking shortly, the probability distribution is represented by an array of 256 real values, one per one value of x – i.e. the normalized histogram. This histogram is learned during the work by a gradient ascent method, i.e. one iteration of the working loop consists in the recalculation

$$p(x)^{(new)} = p(x)^{(old)} \cdot (1-\gamma) + p(x)^{(best)} \cdot \gamma, \tag{16}$$

for $x = 0 \ldots 255$, where $p(x)^{(best)}$ are the "best" values, which are estimated according to Maximum Likelihood principle. This model has only one option

`step=0.1`
: The step size γ in (16).

`Shading`

This model assumes, that there is an "ideal" field of feature values, where the values in two neighboring pixels (according to the 4-neighborhood) differ not more, then some predefined constant. This unknown "ideal profile" of feature values is considered as a field of hidden variables and modelled by the following Gibbs probability distribution. Let us denote by $c : R \to \mathbb{Z}$ the field of hidden variables, let as usual $x : R \to \mathbb{R}$ denote values,

stored in the associated `Map`. The probability of a pair (c, x) is

$$p(c,x) \sim \prod_{rr' \in E} g\big(c(r), c(r')\big) \cdot \prod_{r \in R} q\big(x(r), c(r)\big), \tag{17}$$

where

$$g(c,c') = \begin{cases} 1 & \text{if } |c-c'| \le \delta \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

In this model the Gaussian is used for q:

$$q(x,c) = p(x|c) = \frac{1}{\sqrt{2\pi}\sigma} \exp\Big[-\frac{(c-x)^2}{2\sigma^2}\Big]. \tag{19}$$

One iteration of the working loop consists of a generation step for the field c (one iteration of the Gibbs Sampler), followed by the learning step for σ. The latter is learned in a gradient ascent way similar to (14). The options of this model are:

`init_mode=0`
: Controls the initialization of the field c. Possible values are:

  `0` All values $c(r)$ are set to `mean` (see below).

  `1` The initial field c is chosen in such a way, that it satisfies the conditions (18) and "fits good" (in some reasonable sense) the *whole* associated feature map – i.e. the model assumes, that it is visible everywhere.

`mean=128`
: The initial value for $c(r)$ if `init_mode=0`, if `init_mode=1` this option is ignored.

`sigma=1000.`
: The initial value for $2\sigma^2$.

`min_sigma=10.`
: The lower bound for $2\sigma^2$.

`l_q=1.`
: The parameter λ, which is used to control the behavior of the dispersion during the learning (see (14)).

`jump=1`
: The maximal difference of values in two neighboring pisels – i.e. δ in (18).

`step=0.1`
: Step size λ in (14).

Gshading

This model is a kind of superposition of `General` and `Shading`. As in the `Shading` there is an unknown slowly varied field c, which represents "value shift". The conditional probability distribution $q(x, c)$ is in contrast not the Gaussian, but a general probability distribution of the "shifted" value $(x - c)$. Summarized, the model is

$$p(c, x) = \prod_{rr' \in E} g\big(c(r), c(r')\big) \cdot \prod_{r \in R} q\big(x(r) - c(r)\big), \tag{20}$$

where the function $g(c, c')$ is just the same, as in `Shading`, i.e. (18), function $q(x, c) = p(x - c)$ is a general probability distribution. During the working loop fields c are generated according to the a-posteriori probability distribution $p(c|x)$ by the Gibbs Sampler. The probability distribution q is learned using Expectation Maximization algorithm in an gradient ascent way (like in (16)). It is easy to see, that the Maximum Likelihood formulation is ambiguous, when learning/generating both c and q without further restriction. Therefore the field c is normalized after each M-step to have the mean value equal zero. The field c is initialized with constant zero value, the probability distribution q as uniform probability distribution. The options are:

`jump=1`
: The parameter δ in (18).

`step=0.01`
: The step size γ in (16).

Texture

This model is a realization of ideas, given in [12]. This model is rather complex, therefore we omit here a detailed description. The main idea is, that the texture can be represented by a "template", which can be understood an "elementary texture element". A textured image (or a textured segment) is characterized by a spatial distribution of templates over the field of view. The template itself is a set of elements, which are organized in an orthogonal grid (like pixels in an image). To each element a Gaussian probability distribution of grayvalues is attached, i.e. each element is characterized by its mean greyvalue and dispersion. The options of this model are:

`height_e=16`
: The height of the texture template.

`width_e=16`
: The width of the texture template.

`s_g=4.`
: The above mentioned distribution of templates over the field of view is modeled by a Gibbs probability distribution of second order. This parameter controls, "how regular" should be this distribution. Small values (about 1.) correspond to very regular textures, big values (`s_g`≈`height_e` or `width_e`) correspond to a weak regularity. For `s_g`$\rightarrow \infty$ the model nears to the simple mixture of Gaussians with equal weights.

`l_q=1.`
: The parameters of the template elements (mean values and dispersions) are learned during the working loop in an unsupervised manner. Note, that the learning step for this model is performed by a special function, which is called once per `n_update` iterations of the working loop. The option `l_q` controls the behavior of dispersions (similar to (14)).

`init_min=50`
: The mean values of the template elements are initialized randomly and uniformly in the range `init_min` to `init_max`.

`init_max=200`
: See above.

`min_sigma=1.`
: The lover bound for the dispersions of the template elements.

`step=0.01`
: Step size for learning of the template elements (for both mean grayvalues and dispersions), similar to (14).

This model has its own "shading" part, which allow the mean grayvalues to (slowly) vary over the field of view. The optimization of the shading part is performed in each iteration of the working loop pixelwise as follows. In a pixel r the new value of shading is calculated as a convex combination of the following components:

- The value, that fits as best as possible the feature value (stored in the associated `Map`) at the position r;
- The actual shading value;
- The shading values of neighboring pixels.

The following three options are coefficients of this convex combination. After these options are set, they are normalized to sum to 1.

`shad_next=1.`
: The more, the faster the shading converges.

`shad_prev=100.`
: The more, the slower the shading converges.

`shad_neigh=1000.`
: The more, the smoother is the shading profile.

5 Interface

5.1 Setting the options

5.1.1 Models

Technically the options are transferred to the models by passing a string, which describes the passed options according to the following simple syntax:

`<option>:<value> [<option>:<value> ...]`
The string consists of fields, each one describing one option. The fields are separated by empty spaces. The order of fields can be arbitrary. `<option>` is the name of the option, described by this field (e.g. `n_update`, `l_q`, `Type` etc.). `<value>` is the value of the option, which can be either a number or a string. There are some examples:

`Name:segm1 Type:Split Parent:root potts:3`
This string describes the non-terminal model of the type `Split` named `segm1`, whose parent model (in the model tree) has the name `root`. The Potts parameter a in (8) is set to 3. All other options are set to defaults.

`Type:Background Parent:segm Name:b1 mean:100 Map:image`
This string describes the terminal model of the type `Background` named `b1`, whose parent model has the name `segm`. The initial mean value μ in (13) is set to 100. This model refers to the feature map named `image`. All other options are default.

5.1.2 Feature maps

The feature maps are described in a similar manner, i.e. by a string like

`Type:Map <option>:<value> [<option>:<value> ...]`
(the key field `Type:Map` is used to distinguish `Maps` from models). There is an example:

`Type:Map Name:red File:something.png code:1`
This string describes the feature map named `red`, which stores the values from the red channel (determined by `code:1`) of the image `something.png`.

```
Name:segm Type:Split ...
Name:s1 Parent:segm Type:Background ...
Name:s2 Parent:segm Type:Background ...

Learn:s1 0 0 34 51
Learn:s1 0 100 21 132
Learn:s2 200 58 220 70
```

Figure 3: Example – how to define learning information.

5.1.3 Adding the learning information

As already mentioned, each non-terminal model can have a block of learning information, which gives the possibility to fix segments in particular pixels. This block consists of elements, each one describing a rectangular area of the processed image, where a segment should be fixed. One such rectangle is set by passing to a model of a string of type:

`Learn:<child_name> <x_left> <y_top> <x_right> <y_bottom>`
`<child_name>` is the name of a child model, whose label should be fixed. `<x_...>` and `<y_...>` are the rectangle coordinates. In fig. 3 an example is given. It describes a segmentation (model `segm`) into two segments called `s1` and `s2`, which are Gaussians. There are three rectangular areas, where the segments should be fixed – two rectangles for the segment `s1` and one for the segment `s2`.

- It is assumed, that `x_left`$\leq$`x_right` and `y_top`$\leq$`y_bottom` holds. Otherwise the rectangle is empty.
- Segments are fixed inside the corresponding rectangles inclusive borders. For example a rectangle with `x_left=x_right` and `y_top=y_bottom` is just a single pixel.
- If rectangle coordinates lay out of the image, this rectangle is cropped.
- If there are pixels, which are covered by many learning rectangles, the last occurring `<child_name>` is used to fix segment in these pixels.

5.2 Output

As already mentioned there is an `Interface` object, which is a tool for storing and visualization of the results. At the moment it provides a feedback only, i.e. it does not

allow interactions between the user and the system. Technically, the output is described by a couple of strings, each one defining one "elementary" output. There are two types of "elementary" outputs, that are managed by `Interface`.

5.2.1 Text-output

One elementary text-output is a string (we will call it output-string), which contains option values for a particular model. Each model forms this string in its own way, depending on its options. Here is an example:

```
Name:main timeout:40 gen_count:98 nobj:2 nlearn:2 potts:5
```

Some fields of the output-string describe options of the model, other are variables, which are usefull for debugging. For instance `gen_count` is the number of iterations of the working loop, performed so far. One elementary text-output is defined by a string as follows:

```
Output:Text Name:<name> [File:<file>] [Format:<format>]
```

`Output:Text`
: The key field to identify an elementary text-output.

`<name>`
: The name of the model, which should provide the output-string. This field is mandatory.

`<file>=out_<name>.log`
: This is the file name, where the string should be stored. If `<file>` is `cerr` or `cout` the string is sent to the standart error stream or standart output stream respectively.

`<format>=<empty string>`
: This is the comma separated list of options/variables, which the output-string should contain. If this field is absent, all options are given.

5.2.2 Image-output

Each model provides images to visualize results. One elementary image-output is described by a string like follows:

```
Output:Image Name:<name> code:<code> File:<file>
```

`Output:Image`
: The key field to identify an elementary image-output.

`<name>`
: The name of the model, which should provide the image. Mandatory.

`<code>=1`
: The number, which identifies, what for image should be retrieved. Allowed numbers are: 1, 2, 3, -1 and -2. Each model interprets the code in its own way. Thereby not all codes are supported by all models. The table below summarizes, which codes are supported by which models at the moment:

	1	2	3
`Split`	+	+	?
`SplitR`	?	-	-
`Modalities`	?	-	-
`Weight`	-	-	-
`Background`	-	-	-
`Mix`	-	-	-
`General`	-	-	-
`Shading`	+	-	-
`Gshading`	+	-	-
`Texture`	+	+	+

: ? means, that a modell supports this code only, if there is no models of type `General` in its subtree. The codes -1 and -2 are supported by all models but they are mainly for debugging purposes.

`<file>=out_<name>_<code>.png`
: The file name to store the image. The image format is always `png` (does not depend on the extention).

5.3 Error messages

Since the interactions with user are not allowed yet, there is practically no other way to handle errors, than simply to abort the program. In that case an error description is printed out in the following format:

```
ObjName :  <name of the element>
error   :  <a general error description/diagnostic>
FnName  :  <name of function>
ObjInfo :  <object information>
Message :  <a hint>
```

The meanings of the description parts are obvious. Here is a pair of examples:

```
ObjName :  main
error   :  Unknown field (code=4)
FnName  :  Split::Split()
ObjInfo :  Name:main reset_policy:31 n_update:0 timeout:40
min_timeout:1 gen_count:0 nobj:2 nlearn:2 Type:Split
potts:10
Message :  pott:5.
```

In this example the description string contains the syntax error, namely `pott:5.` instead of `potts:5.` is written.

```
ObjName :  image
error   :  Load (code=2)
FnName  :  Map::Map()
ObjInfo :  Name:image reset_policy:31
Message :  Probably could not load tentacke.png
```

In this example the file name was set not correctly. Therefore the input image could not be loaded.

6 Examples

6.1 Program `objsegm_simple`

The program `objsegm_simple` can be seen as a simplest example, which illustrates, how the system `objsegm` can be used. The usage of the program is following:

```
objsegm_simple <description file> [<option> ...]
```

`<description file>` is the name of a text file, where the description of a complex model is given (as well as all other options, needed for `objsegm_simple`). This file consists of lines, each line can be one of the following:

`# <arbitrary text>`
: The lines, which start with `#` are comments.

`END`
: The lines, following this one are ignored. They can be used e.g. to store some old experiments, comments, notations etc. The line `END` is not mandatory, i.e. the description file is processed until the end of file if there is no such string.

`<model/interface/map/parameter/learning string>`
: The description string for a model (an elementary output, feature map, parameter, learning item correspondingly). They describe element options according to the format given in section 4.

`<objsegm_simple option>`
: The program `objsegm_simple` has its own options (which do not relate to the model tree). These are

  `Time=-1`
  : The time to work in seconds. The default value "-1" means infinity. The string, describing this option looks like

    `Time:<number>`

  `dtime=10`
  : The "output" activities of the `Interface` object are performed once per each `dtime` seconds. The description string is

    `dtime:<number>`

The order of lines is arbitrary. Each line can start or end with empty spaces, the fields in a line can be separated by multiple spaces (the parser of `objsegm_simple` removes unnecessary spaces). For convenience, the description file can be simplified in addition in the following way to avoid repetitions of option values, which are common for many elements. The following substitution is allowed. A couple of lines, which have common parts, i.e. which look like

```
<prefix> <line 1> <suffix>
<prefix> <line 2> <suffix>
...
<prefix> <line n> <suffix>
```

can be replaced by

```
<prefix> {
      <line 1>
      <line 2>
      ...
```

```
      <line n>
} <suffix>
```

- The opening bracket "{" should be attached to the <prefix>. The part of the <prefix>-line, which is located right to the "{", is ignored.
- The <suffix> should be in the same line as the closing bracket "}". The part of the <suffix>-line, which is located left to the "}" is ignored.
- Indentation is not necessary.
- Both <prefix> and <suffix> may be empty.

Here is a simple example:

```
Parent:main Type:Background {
      Name:b1 mean:100
      Name:b2 mean:150
} Map:image
```

This block describes two segments, which are of the same type Background, have common parent main and refer to the same feature map image.

The program objsegm_simple realizes also a possibility to transfer options by the commandline. It is very usefull to perform experiments in a batch mode. The options, given in the commandline have format

<name>:<option>:<value>

They override those, given in the description file. The options, given in the commandline, can be model options or the program options only, i.e. neither options for Maps nor for Interface nor learning information nor Parameter options.

The program objsegm_simple proceeds as follows:

1. First of all the description file and the commandline are parsed. Thereby the parser of objsegm_simple does not check the syntax completely. It only makes substitutions (see above), merges together options from the description file and the commandline options (if any) and separates lines by the element types (models, Parameters, Maps etc.) – i.e. it only prepares lines for transferring to corresponding elements.

2. Then `Maps` are constructed (input images are loaded, preprocessing activities are performed etc.).

3. The next step is the construction of the model tree. At this stage all description lines are transferred to the corresponding models and `Parameters`. The majority of errors occur just here because in this phase each model parses its options.

4. The `Interface` object is constructed. Thereby the description lines are not parsed but only transferred to the `Interface`.

5. The working loops of all models in the model tree are started. Once per `dtime` seconds the output activities of the `Interface` object are performed. If the description lines for the `Interface` were not correct, the error occurs.

6. – If `Time=-1` the working loops never stop, i.e. the program should be aborted from outside.
   – Otherwise the program finishes after `Time` seconds are elapsed.

6.2 Segmentation examples

In this section we give examples, which illustrate the usage of the system and in particular the program `objsegm_simple`. Before we present the examples we would like to note the following.

As already said our approach is based on statistical modeling. Moreover, most of the used algorithms are mainly not deterministic, but stochastic ones (e.g. the Gibbs Sampler). It means, that the results can be in principle seen as statistical variables itself. Therefore they are in general not fully reproducible – they only "look similar". Summarized, many calls of the program may produce different results. Main source of this irreproducibility are random initialization of almost all components (in particular all segmentations are initialized randomly if there is no learning information, associated with them). Another source is the use of the Expectation-Maximization algorithm for learning. As known, it does not converge in general to the global optima. Consequently "a reasonable" initialization of learned parameters is very usefull to make the results reproducible.

For each presented example we give the corresponding description files, used by the program `objsegm_simple`. Among other things there are many parameters/options, which influent "convergence speed" of the method (mainly the `step` option) as well as the synchronization of model parts (e.g. `timeout`-s). In some cases these options influent not only the speed of convergence but the results as well. We performed our experiments mainly on a two processors computer with `AMD64 X2`. Consequently all options are

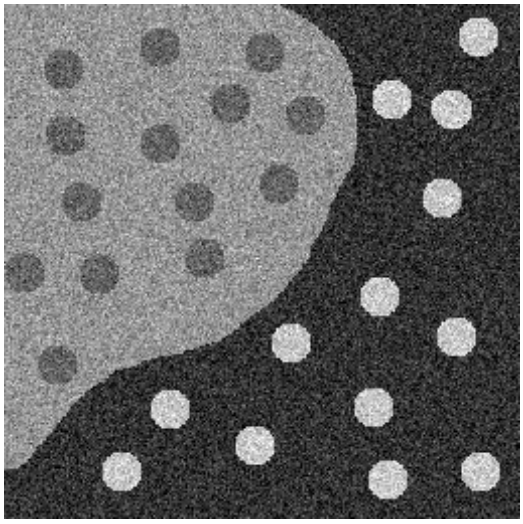


Figure 4: Artificial example – original image.

tuned to reach good results/reproducibility just on this computer. Eventually they should be changed accordingly if working on other platforms.

The parameter `Time` in presented examples is set to a relatively big number to ensure a segmentation, which is "the best one in scope of the used model". As a rule, reasonable results occur much earlier. In addition the time of generation can be essentially reduced, if the learning of unknown parameters starts from a good initialization.

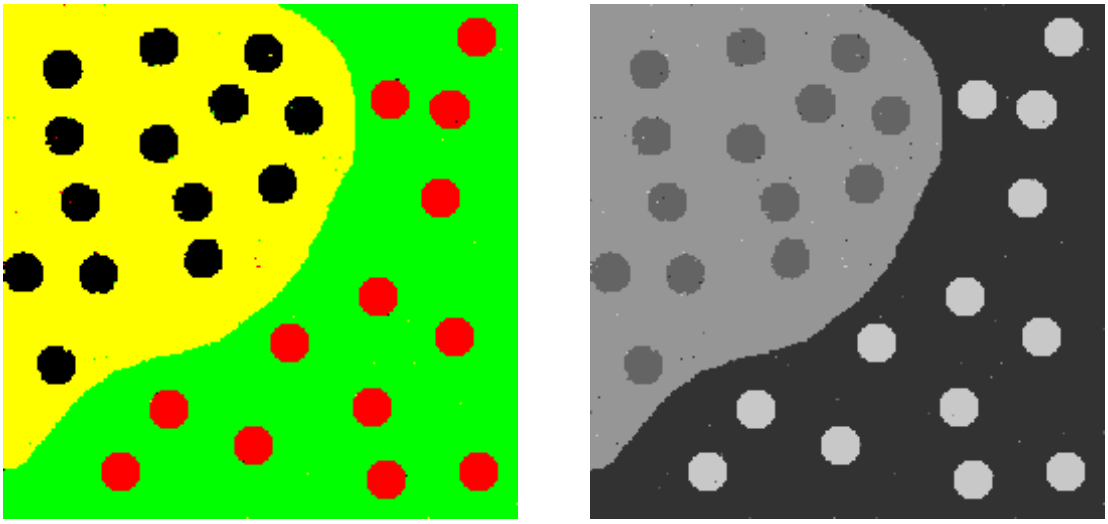
We begin with a very simple artificial example, given in fig. 4. The segmentation was painted manually, segments were then filled with constant grayvalues. Finally the Gaussian noise was added.

Obviously it is possible to build different (less or more) appropriate segmentation models for such a kind of images. One possibility would be to segment them into four segments each one being a Gaussian – i.e. in the same manner, as the image in fig. 4 was produced. The corresponding description file is given in fig. 5. The Gaussians were learned in fully unsupervised manner – no learning information was given and all Gaussians were initialized with default values. The images, produced by the root model `main` are given in fig. 6. The "denoised" image is produced by replacing in each pixel the original grayvalue by the mean value of corresponding Gaussian.

Another way (may be not so appropriate but faster) is to segment the image into only two segments, assuming a Gaussian mixtures for both segments. The corresponding description file is given in fig. 7. In this case we initialized the mean values of Gaussians with true ones (which were used to produce the original image). The option `step` is set to

```
Time:1000
dtime:2
Type:Map Name:image File:test5_20.png code:0
Type:Split Name:main potts:15 timeout:0
Type:Background Map:image Parent:main {
    Name:b1
    Name:b2
    Name:b3
    Name:b4
} step:0.1
Output:Text File:cerr {
    Name:main
    Name:b1
    Name:b2
    Name:b3
    Name:b4
} Format:Name,gen_count,timeout,mean,sigma
Output:Image Name:main {
    code:1
    code:2
    code:3
}
```

Figure 5: Description file for the artificial example (four Gaussians).



(a) Segmentation into four segments (`code:2`)

(b) "Denoised" image (`code:3`)

Figure 6: Results for the artificial example (four Gaussians).

a very small value, which corresponds to "almost no learning". The images, produced by the root model are presented in fig. 8. The "denoised" image contains grayvalues, which are the weightet sum of mean values of Gaussians from corresponding mixtures.

Finally, the same scene can be modeled in an hierarchical manner: it consists of two segments, each one consisting itself of two segments. The terminal models are Gaussian. The corresponding description file is presented in the fig. 9. In that case it was also possible to learn Gaussians in fully unsupervised manner without to violate the reproducibility (up to the permutation of segments). The images, produced by the non-terminal models are given in fig. 10. The "denoised" image is not shown since it looks very similar to that in fig. 6.

The next is an example of texture segmentation – see fig. 11. We should admit, that here it was necessary to tune the parameters of textures very carefully. But with this parameters the segmentation were done in fully unsupervised manner (inclusive the learning of texture templates). The corresponding description file is given in fig. 12. In fig. 13 the images, produced by the `Texture` models `t1` and `t2` are presented (see [12] for description of image contents).

The last example is an image of a real scene, presented in fig. 14. The corresponding description file is given in fig. 15. It is a good example to illustrate how to take into account colors (in contrast to the above examples, where the input images were grayvalued ones).

```
Time:1000
dtime:2
Type:Map Name:image File:test5_20.png code:0
Type:Split Name:main potts:20 timeout:0
Type:Mix Map:image Parent:main {
    Name:m1 m(0):50  m(1):200
    Name:m2 m(0):150 m(1):100
} step:0.001
Output:Text File:cerr Format:Name,gen_count,timeout {
    Name:main
    Name:m1
    Name:m2
}
Output:Image Name:main {
    code:1
    code:2
    code:3
}
```

Figure 7: Description file for the artificial example (two mixtures).

(a) Segmentation into two segments (`code:2`)

(b) "Denoised" image (`code:3`)

Figure 8: Results for the artificial example (two mixtures).

```
Time:6000
dtime:2
Type:Map Name:image File:test5_20.png code:0
Type:Split Name:main potts:20
Type:Split Parent:main potts:10 {
    Name:s1
    Name:s2
}
Type:Background Map:image {
    Parent:s1 {
        Name:b1
        Name:b2
    }
    Parent:s2 {
        Name:b3
        Name:b4
    }
} step:0.1
Output:Text File:cerr {
    Name:main
    Name:b1
    Name:b2
    Name:b3
    Name:b4
} Format:Name,gen_count,timeout
Output:Image {
    Name:main {
        code:1
        code:2
        code:3
    }
    Name:s1 code:2
    Name:s2 code:2
}
```

Figure 9: Description file for the artificial example (hierarchical segmentation).

(a) `Name:main code:2` (b) `Name:s1 code:2` (c) `Name:s2 code:2`

Figure 10: Results for the artificial example (hierarchical segmentation).

Here it is assumed, that RGB-channels of the image are conditionally independent (modeled by `Modalities`). Unfortunately it was very difficult for this example to reach good and reproducible segmentation in fully unsupervised manner. Therefore learning information was included. The "reconstructed" image in fig. 14.c) is produced by subtracting for each pixel its "shading" part (see description of `Gshading`).

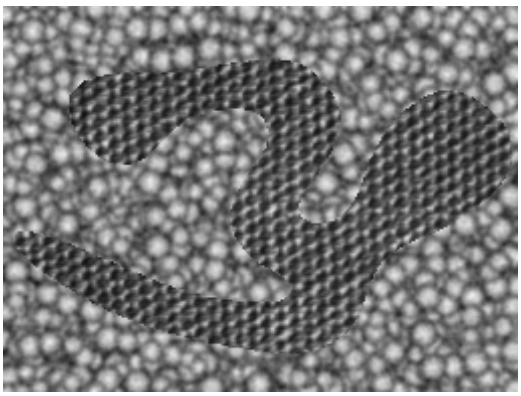
7 Conclusion

First of all we would like no note, that the system `objsegm` is still in progress. To say frankly, we do not think, that in the closest time the system will be in such a state, that an "ordinary user" could use it without going deep in the theory. This is the case, because only at the moment this theory becomes less or more practicable.

Here is a short list of future work:

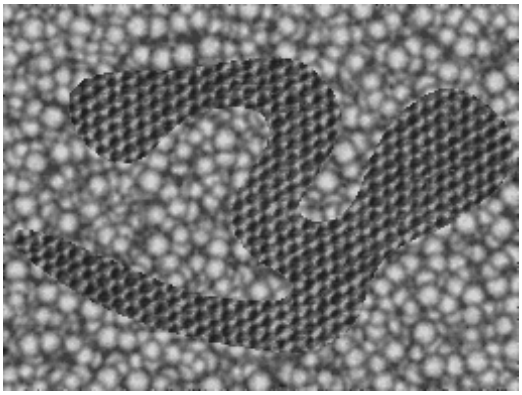
- First of all we would like to precise the notation of `Parameter`. As already said, they can be seen as a kind of mechanism, which allow to influent statistical models non locally. At the moment there are still many open questions, both theoretical and practical ones: how to learn such a kind of parameter, what is common for all parameter of such kind etc. Therefore in this user manual we only mentioned this mechanism, but not documented them.

- From the technical side, the system should give the user more possibilities for interactions. In particular interactions during the work should be allowed. Functions for storing and loading of models should be implemented.



(a) Original image

(b) Segmentation



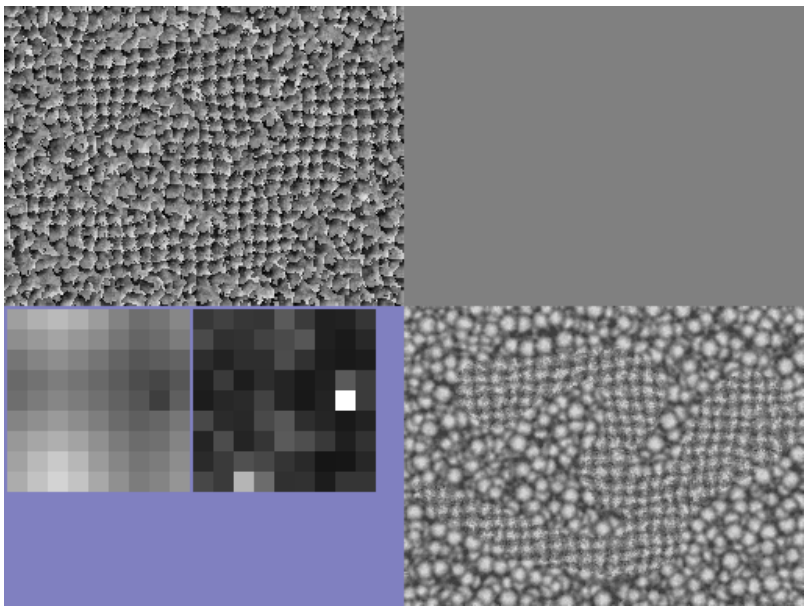
(c) “Reconstructed” image

Figure 11: Example “tentacle”.

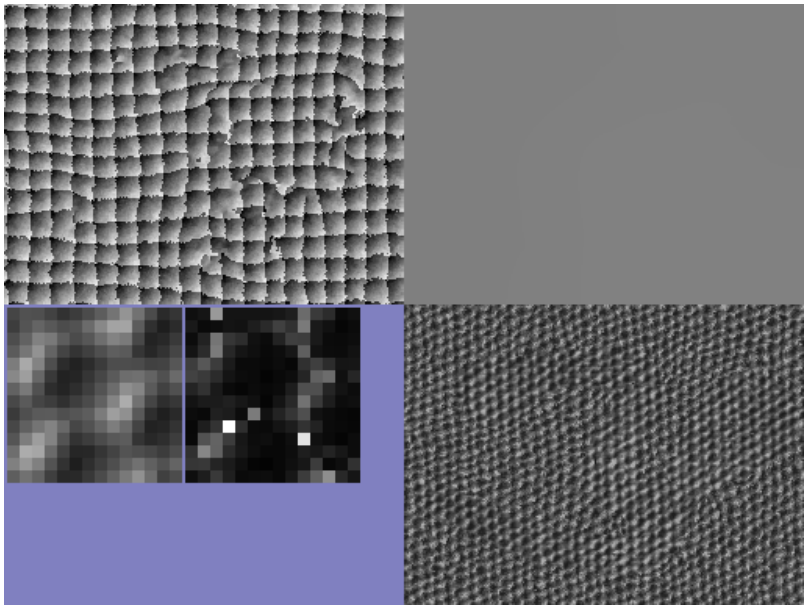
```
Time:15000
dtime:60
Name:image Type:Map File:tentacle.png code:0
Output:Image {
    Name:main {
        code:1
        code:2
        code:3
    }
    Name:t1
    Name:t2
}
Output:Text File:cerr {
    Name:main
    Name:t1
    Name:t2
} Format:Name,n_update,gen_count,timeout

Name:main Type:Split Parent: potts:11. timeout:40
Type:Texture Parent:main Map:image {
    Name:t1 height_e:9 width_e:9 s_g:4.
    Name:t2 height_e:14 width_e:14 s_g:2.
} step:0.1 n_update:10 min_timeout:0 shad_neigh:500
```

Figure 12: Description file for the example “tentacle”.



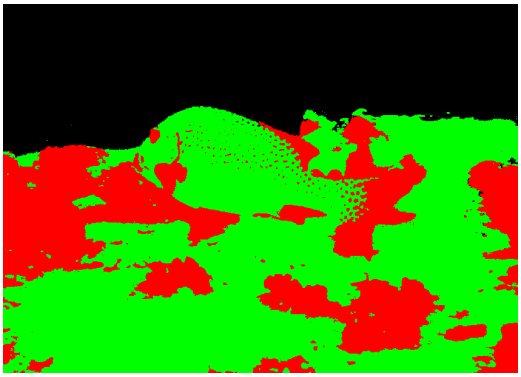
(a) First texture



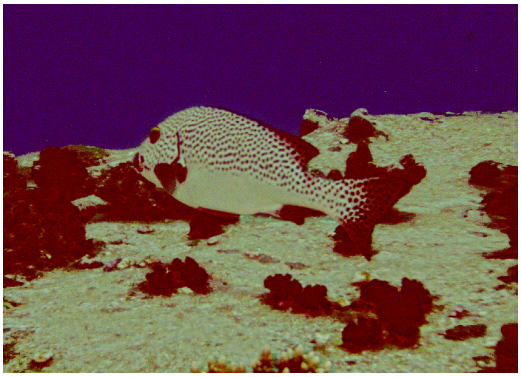
(b) Second texture

Figure 13: Example “tentacle” – texture images.

(a) Original image



(b) Segmentation



(c) “Reconstructed” image

Figure 14: Example “fish”.

```
Time:6000
Output:Image Name:main code:2
Output:Image Name:main code:3
Output:Text File:cerr Name:main
Type:Map File:fisch_e.ppm {
    Name:image_red   code:1
    Name:image_green code:2
    Name:image_blue  code:3
} Format:Name,timeout,gen_count
Name:main Type:Split potts:6 timeout:400 n_update:100
Parent:main Type:Modalities min_timeout:10 {
    Name:t1
    Name:t2
    Name:t3
}
Type:Gshading jump:3 step:0.01 min_timeout:10 {
    Parent:t1 {
        Name:t1_r Map:image_red
        Name:t1_g Map:image_green
        Name:t1_b Map:image_blue
    }
    Parent:t2 {
        Name:t2_r Map:image_red
        Name:t2_g Map:image_green
        Name:t2_b Map:image_blue
    }
    Parent:t3 {
        Name:t3_r Map:image_red
        Name:t3_g Map:image_green
        Name:t3_b Map:image_blue
    }
}
Learn:t1 4 5 846 162
Learn:t2 14 321 100 400
Learn:t2 625 480 686 521
Learn:t3 674 371 771 448
Learn:t3 115 516 414 564
Learn:t3 650 193 840 240
```

Figure 15: Description file for the example “fish”.

– The main idea of our approach is, that "complex" models can be built using a relatively small number of simple "base" models in an hierarchical manner – i.e. a complex model is a tree-like structure. This reminds of the notation of two-dimensional grammars (see e.g. [8]). A segmentation model can be understood in this context as a derivation rule. The main difference from the two-dimensional grammars (in our opinion) is the fact, that in our method the tree-like structure of a complex model is fixed. Therefore the hierarchical segmentation approach can be seen as an intermidiate stage between labeling problems and two-dimensional grammars. The question arises, whether it is possible to extend hierarchical segmentations in such a way, that the structure of a complex model need not to be fixed.

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